

Last class: MC for generating a random matching for any graph  $G=(V,E)$ .

Today: Random perfect matching of any bipartite graph  $G=(L \cup R, E)$   
↑ all edges b/w L & R.

— Estimating # of perfect matchings  
Corresponds to 0-1 permanent.  
(extends to non-negative permanents)

For a graph  $G=(V,E)$   
let  $M$  = all matchings of  $G$ .

To generate a random matching, defined a Markov chain on  $M$ .

To generate a random perfect matching we'll define a MC on  $P \cup N$  where

$P$  = all perfect matchings

&  $N$  = all near-perfect matchings  
= matchings with exactly 2 unmatched vertices

MC on  $\Omega = \mathcal{P}(V)$ :

From  $X_t \in \Omega$ ,

1. Choose  $e = (v, w) \in E$  var.

2. If  $X_t \in N(v, w)$  then set  $X' = X_t \cup e$ .

3. If  $e \in X_t$  then set  $X' = X_t \setminus e$ .

4. If  $X_t \in N(v, z)$  for  $z \neq w$ , then  
set  $X' = X_t \cup e \setminus (w, y)$   
for  $(w, y) \in X_t$ .

5. If  $X'$  is defined &  $X' \in \Omega$  then  
with prob.  $\frac{1}{2}$  set  $X_{t+1} = X'$   
else  $X_{t+1} = X_t$ .

We argued (roughly) that if  $\pi(\mathcal{P}) \geq \frac{1}{n^2}$  then

$T_{\text{mix}} = \text{poly}(n)$  & we can generate  
a random perfect matching in  $\text{poly}(n)$  time.

Moreover, if  $\text{degree}(v) > \frac{n}{2}$  for all  $v \in V$ ,

then  $\pi(\mathcal{P}) \geq \frac{1}{n^2}$ .

Introduce weights on matchings which depends on the hole pattern.

Say every  $M \in \Omega$ , has a weight  $w(M) > 0$ .  
How to sample from  $\pi(M) = \frac{w(M)}{Z}$ ?

Same chain as before change step 5 to:

5. Set  $X_{t+1} = X'$  w.p.  $\min\left\{1, \frac{w(X')}{w(X_t)}\right\}$

& o/w  $X_{t+1} = X_t$ .  
Metropolis filter

What weights?

Bipartite graph with  $V = L \cup R$ .

~~For let  $N$~~

For  $v \in L, w \in R$ , let  $N(v, w) =$  near-perfect matchings with unmatched vertices  $v \in L, w \in R$ .

thus,  $N = \cup_{v \in L, w \in R} N(v, w)$ .

&  $\Omega = \mathcal{P} \cup_{v, w} N(v, w)$

For  $M \in \mathcal{P}$ , let  $w(M) = 1$

For  $M \in \mathcal{N}(y, z)$ , let  $w(M) = w(y, z) = \frac{|\mathcal{P}|}{|\mathcal{N}(y, z)|}$

So  $n^2 + 1$  different weights  
for graph with  $n + n$  vertices.

Note,  $w(\mathcal{N}(y, z)) = \sum_{M \in \mathcal{N}(y, z)} w(M) = |\mathcal{N}(y, z)| \times \frac{|\mathcal{P}|}{|\mathcal{N}(y, z)|} = |\mathcal{P}|$ .

&  $w(\mathcal{P}) = |\mathcal{P}|$ .

Thus,  $\pi(\mathcal{N}(y, z)) = \pi(\mathcal{P}) = \frac{1}{n^2 + 1}$ .

Moreover with these weights,

$T_{\text{mix}} = O(n^5 \log n)$ , for any bipartite graph.

Thus, in  $\text{poly}(n)$  time can find a random perfect matching.

Why is it rapid mixing?

(5)

Congestion for  $M \rightarrow M'$ :

$$\rho(M, M') = \frac{1}{\pi(M)P(M, M')} \sum_{(I, F) \in \mathcal{P}_{M, M'}} \pi(I)\pi(F)$$

Note,  $\pi(M)P(M, M') = \pi(M')P(M', M)$

assume  $\pi(M) \leq \pi(M')$

$$\text{Then } P(M, M') = \frac{1}{2m \leftarrow m = |E|}$$

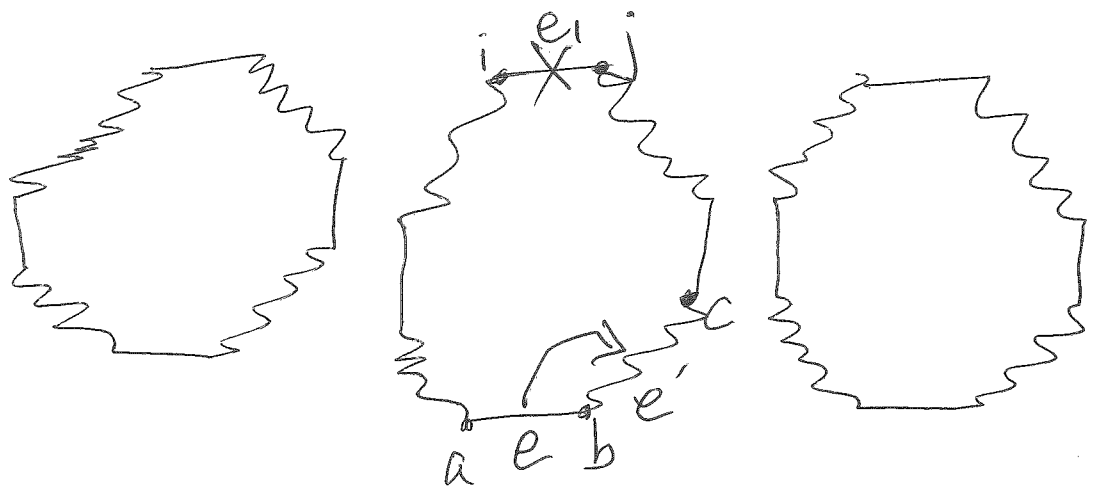
$$\text{So, } \rho(M, M') = \frac{1}{2\pi(M)m} \sum_{(I, F) \in \mathcal{P}_{M, M'}} \pi(I)\pi(F)$$

define  $\mathcal{C} = \mathcal{N} : \mathcal{P}_{M, M'} \rightarrow \mathcal{C}$  where

encoding  $C$  where  $\pi(I)\pi(F) \leq \pi(M)\pi(C)$ ,

$$\text{then } \rho(M, M') \leq \frac{1}{2m} \sum_{C \in \mathcal{C}} \pi(C) \leq \frac{1}{2m} 2m = 1$$

Consider  $\underbrace{I, F \in \mathcal{P}}_m \simeq I \oplus F$ :



Note  $M \oplus C$  has same edges as  $I \oplus F$   
 except 1<sup>st</sup> edge  $e_1$  of  
 current cycle  
 & one edge  $e'$  in  
 current slide.

Thus,  $\pi(M) \pi(C) \geq \lambda^2 \pi(I) \pi(F)$

& hence  $\rho \leq O(m \lambda^2)$ .

too much! Since  $\lambda \approx \frac{1}{n!}$  at end.

Suppose  $\lambda=0$ , so  $w(y,z) = \frac{|\theta|}{|N(y,z)|}$

(5c)

Consider  $I, F \in \mathcal{P}$  so  $w(I)w(F) = 1$ .

For  $M \rightarrow M'$ , we have  $M \in N(i,c)$   
&  $C \in N(j,b)$

Note,  $(i,j) \in E$  &  $(b,c) \in E$

& it also holds that:

$$\boxed{|N(i,c)| \times |N(j,b)|} \leq |\theta|^2$$

when  $(i,j), (b,c) \in E$

Thus,  $w(i,c)w(j,b) \geq 1$

&  $w(M)w(C) \geq w(I)w(F)$ .

□

In general, for  $\lambda > 0$ ,

$$\lambda(N(i,c))\lambda(N(j,b))\lambda(i,j)\lambda(b,c) \leq \lambda(\theta)^2$$

Thus,  $w(I)w(F) = 1 \leq \frac{w(i,c)w(j,b)}{\lambda(i,j)\lambda(b,c)}$ .

How to find these weights?

Consider  $K_{n,n}$  (complete bipartite graph)

where edges of  $G$  have activity 1

& non-edges of  $G$  have activity  $\lambda$

for some  $0 \leq \lambda \leq 1$ .

In other words, for  $v \in L, z \in R$ ,

$$\lambda(v,z) = \begin{cases} 1 & \text{if } (v,z) \in E \\ \lambda & \text{if } (v,z) \notin E \end{cases}$$

then for matching  $M \in \mathcal{M}$ ,

$$\lambda(M) = \prod_{e \in M} \lambda(e).$$

If  $\lambda = 1$ , then all  $n!$  perfect matchings of  $K_{n,n}$  have activity 1.

If  $\lambda = 0$ , then every  $M \in \mathcal{P}$  has activity 1  
&  $M \notin \mathcal{P}$  has activity 0

So  $\lambda(\mathcal{P}) = |\mathcal{P}|$  when  $\lambda = 1$ .



⑦

Generalize weights to:

$$w(y, z) = \frac{\lambda(\theta)}{\lambda(N(y, z))}$$

$$\text{where } \lambda(\theta) = \sum_{M \in \theta} \lambda(M) = \sum_{M \in \theta} \prod_{e \in M} \lambda(e)$$

$$\& \lambda(N(y, z)) = \sum_{M \in N(y, z)} \lambda(M)$$

thus if  $\lambda = 0$  then  $\lambda(\theta) = |\theta|$

$$\& \lambda(N(y, z)) = |N(y, z)|$$

$$\text{so } w(y, z) = \frac{|\theta|}{|N(y, z)|} \text{ if } \lambda = 0$$

$$\& \text{if } \lambda = 1 \text{ then } w(y, z) = \frac{n!}{(n-1)!} = n$$

Hence, weights are easy to compute when  $\lambda = 1$

& when  $\lambda = 0$  then they give  
a random perfect matching.

(Note  $\lambda = \frac{1}{n!}$  is roughly equivalent to  $\lambda = 0$ )

Suppose we had wrong weights  $\hat{\omega}(y, z)$   
(so  $\hat{\omega}(y, z) \neq \frac{\lambda(\rho)}{\lambda(N(y, z))}$ )

What is the stationary distribution  $\hat{\pi}$   
for MC run with these  $\hat{\omega}$ ?

$$\begin{aligned}\text{Then } \hat{\pi}(\rho) &= \lambda(\rho) = \sum_{m \in \rho} \lambda(m) \\ \hat{\pi}(N(y, z)) &= \sum_{m \in N(y, z)} \lambda(m) \hat{\omega}(y, z) \\ &= \hat{\omega}(y, z) \lambda(N(y, z))\end{aligned}$$

Run the MC many times & look at  
fraction of samples that are in  $\rho$   
to those in  $N(y, z)$ ,

$$\text{then } \frac{\hat{\pi}(\rho)}{\hat{\pi}(N(y, z))} = \frac{\lambda(\rho)}{\hat{\omega}(y, z) \lambda(N(y, z))} = \frac{\omega(y, z)}{\hat{\omega}(y, z)}$$

So this ratio tells us how far  $\hat{\omega}$  is off  
from  $\omega$ .

Again,  $w(y, z) = \hat{w}(y, z) \frac{\hat{\pi}(P)}{\hat{\pi}(N(y, z))}$ .

Suppose,  $\frac{w(y, z)}{2} \leq \hat{w}(y, z) \leq 2w(y, z)$  (\*)

then  $\frac{\hat{\pi}(P)}{4} \leq \hat{\pi}(N(y, z)) \leq 4\hat{\pi}(P)$

So with  $O(n^2 \log n)$  samples we can estimate  $w(y, z)$  using

Start with  $\lambda = 1$ . Compute  $w(y, z)$  for all  $y \in L, z \in R$ .

- Set  $\hat{w}(y, z) = w(y, z)$  for all  $y \in L, z \in R$ .

- Set  $\lambda = \frac{\lambda}{2}$

- Run MC with  $\lambda$  &  $\hat{w}$  & then generate  $O(n^2 \log n)$  samples from  $\hat{\pi}$  & estimate  $w(y, z)$ .

Repeat, until  $\lambda \leq \frac{1}{n}$ .

Overall running time:  $O^*$  ignores log factors.

-  $O^*(n^4)$  time per sample

-  $O^*(n^2)$  samples per round

-  $O^*(n^2)$  rounds



$\Rightarrow O^*(n^8)$  time.

(Can improve this to  $O^*(n)$  rounds.)

$O^*(n^7)$  time is still the best known.